SYNOPSIS

Simulation Study of Particle Detectors for High Energy Physics Experiments

SUBMITTED BY

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1. Title

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2. Introduction

High Energy Physics (HEP) experiments aim to uncover the fundamental structure of matter and the interactions governing elementary particles. Modern collider experiments rely on sophisticated particle detectors to accurately measure the energy, momentum, and identity of particles produced in high-energy collisions. Calorimeter-based detectors, in particular, play a central role in determining the energies of photons, electrons, and hadrons. Their performance directly impacts the precision of physics measurements, including searches for new phenomena.

Simulation frameworks such as **Geant4** have become indispensable tools for modeling detector geometry, studying particle–matter interactions, and evaluating detector performance under various configurations. Alongside traditional reconstruction methods, recent advancements in **Machine Learning (ML)** have shown promise in improving particle identification and reconstruction in calorimeter-based systems.

This research proposes a comprehensive simulation study to investigate how calorimeter geometry influences detector performance and to explore the integration of ML techniques for enhancing particle identification and reconstruction.

3. Review of Literature

Calorimeter detectors have undergone significant development over the past decades to meet the demands of high-energy collider experiments. Foundational work by Wigmans [1] established the fundamental principles of elec-

tromagnetic and hadronic calorimetry, providing detailed insights into shower development, sampling fluctuations, and intrinsic limits of energy resolution. Similarly, Fabjan and Gianotti [2] presented a comprehensive review of calorimeter technologies, emphasizing their importance in precision measurements and particle identification in collider environments.

With the commissioning of high-energy colliders such as the Large Hadron Collider (LHC), calorimeter design requirements became more stringent. The CMS Electromagnetic Calorimeter (ECAL), based on $PbWO_4$ crystals, demonstrated excellent energy resolution for electrons and photons [3]. Subsequent performance studies highlighted challenges related to radiation damage, high pile-up, and stability under varying operational conditions [4, 5]. These studies underscored the need for continuous calibration and motivated ongoing upgrades for high-luminosity environments.

Simulation tools have played a central role in detector R&D. The Geant4 simulation framework, introduced by Agostinelli et al. [6], revolutionized detector modeling by enabling detailed tracking of particle–matter interactions. Further improvements by Allison et al. [7] expanded physics modeling capabilities, geometry construction methods, and optical photon tracking. Numerous detector development efforts, including those of the CALICE Collaboration [8, 9], used Geant4 extensively to study different sampling structures, scintillator–SiPM readout technologies, and high-granularity prototypes. These studies demonstrated that segmentation, tile geometry (square, hexagonal, trapezoidal), and absorber–scintillator combinations substantially influence energy resolution, shower topology, and particle-flow performance.

Future collider experiments have motivated the development of high-granularity calorimeters (HGCAL). The CMS HGCAL Technical Design Report showed that fine segmentation significantly enhances shower separation and improves jet energy resolution under high-luminosity conditions [10]. Test beam and simulation studies confirmed that such detectors offer rich spatial information suitable for advanced reconstruction algorithms [11].

In parallel with hardware innovation, **Machine Learning (ML)** has emerged as a transformative tool in particle detection and reconstruction. Baldi et al. [12] demonstrated that deep neural networks outperform traditional multivariate classifiers for particle identification tasks. Paganini et al. [13] introduced generative adversarial networks (GANs) to emulate calorimeter shower simulations, achieving substantial computational speedups while retaining physical fidelity.

A major application of ML in calorimetry is the separation of prompt photons from neutral pion (π^0) backgrounds. Studies by the ATLAS Collaboration [14] and Sirunyan et al. [15] showed that deep learning models significantly improve discrimination power compared with classical shower-shape-based methods such as R9, cluster widths, and energy ratios. ML-based approaches have also enhanced energy regression, position reconstruction, pile-up mitigation, and particle-flow algorithms, contributing to higher precision in event reconstruction.

Despite these advances, a systematic study integrating geometry-dependent calorimeter performance using Geant4 and ML-enhanced reconstruction remains limited. Existing research typically investigates either geometrical optimization or ML reconstruction independently. Therefore, a combined study that evaluates detector geometry variation, simulation-based performance analysis, and ML-driven particle identification and reconstruction can offer valuable insights for designing next-generation calorimeters for future collider experiments.

4. Statement of the Problem

Calorimeter performance is strongly influenced by material composition, segmentation, and geometrical design. Traditional reconstruction methods often struggle with complexities such as overlapping showers, background contamination, and subtle differences between particle signatures. While ML methods

have shown promise in improving classification and reconstruction, their optimal integration with detector geometry has not been thoroughly explored.

This study therefore seeks to investigate how calorimeter geometry affects detector performance through detailed Geant4 simulations and to examine how ML techniques can enhance particle identification and reconstruction accuracy using simulated data.

5. Objectives

1. To develop Geant4-based simulation models of calorimeter detectors with varying geometrical configurations.
2. To evaluate performance metrics such as energy resolution, spatial resolution, and shower profile characteristics for different geometries.
3. To analyze detector response for photons, electrons, and hadrons using simulated data.
4. To implement ML-based models for particle identification, particularly for separating prompt photons from π^0 backgrounds.
5. To explore ML-driven particle reconstruction techniques and compare their performance with traditional approaches.
6. To identify optimal calorimeter geometries and ML models that enhance overall detector performance.

6. Methodology

The research methodology integrates detailed detector simulation with ML-based analysis.

Geant4 Simulation Framework

A comprehensive simulation environment will be established using Geant4. The calorimeter will be modeled with adjustable geometry, including square, hexagonal, and trapezoidal scintillator tiles coupled with SiPM-based readout. Electromagnetic and hadronic physics lists such as FTFP_BERT will be employed. Simulations will be performed for a variety of particle types and energies relevant to collider environments. Key outputs such as energy deposition, shower development, and hit-level information will be recorded.

Detector Performance Analysis

The simulated data will be processed to compute:

- energy resolution and linearity,
- spatial resolution and position reconstruction accuracy,
- longitudinal and transverse shower shapes,
- geometry-dependent performance variations,
- shower shape variables for classification.

Comparisons across geometries will help identify design parameters that influence detector performance.

Machine Learning for Particle Identification

Deep learning architectures such as CNNs and GNNs will be trained using calorimeter shower images or reconstructed hit maps. Feature-based models (BDTs, Random Forests) will also be explored. The primary classification task will be prompt-photon vs. π^0-decay photon separation. Model performance will be evaluated using accuracy, ROC curves, AUC scores, and confusion matrices.

Machine Learning for Reconstruction

ML regression techniques will be used to improve:

- energy estimation,
- shower position reconstruction,
- corrections for geometric nonlinearities,
- compensation for sampling fluctuations.

Results will be benchmarked against classical reconstruction algorithms.

Optimization and Validation

The findings from simulation and ML analysis will be combined to identify optimal detector geometries and reconstruction strategies. Validation will be performed by comparing results with published performance metrics from experiments such as CMS, ATLAS, and CALICE.

7. Significance of the Study

This study will contribute to the advancement of calorimeter-based detector technologies by systematically exploring geometry-dependent performance using Geant4 simulations and integrating modern ML techniques for improved particle identification and reconstruction. The outcomes are expected to provide valuable insights for next-generation detector design at future collider experiments and support ongoing calorimeter R&D efforts in high-energy physics.

References

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[6] S. Agostinelli et al., “GEANT4—A Simulation Toolkit”, *Nuclear Instruments and Methods A*, 2003.

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[12] P. Baldi, P. Sadowski, and D. Whiteson, “Searching for Exotic Particles in High-Energy Physics with Deep Learning”, *Nature Communications*, 2014.

[13] M. Paganini, L. de Oliveira, and B. Nachman, "Calorimeter Shower Simulation with Generative Adversarial Networks", *European Physical Journal C*, 2017.

[14] ATLAS Collaboration, "Prompt Photon Identification Using Machine Learning", ATLAS Public Note, 2019.

[15] A. M. Sirunyan et al., "Deep Learning-Based Photon Identification in CMS", CMS Physics Analysis Summary, 2020.

Proposed Chapterization

This Ph.D. thesis will be organized into the following chapters:

Chapter 1: Introduction

This chapter will present the overall motivation for the research and introduce the fundamental concepts of particle detectors used in high-energy physics experiments. It will discuss the significance of calorimetry, the challenges faced by modern detector systems, and the essential role of simulation in detector development and optimization. The chapter will outline the research problem, objectives, scope, and structure of the thesis.

Chapter 2: Literature Review

This chapter will provide a detailed review of existing studies related to calorimeter-based detectors, detector geometry optimization, and simulation work using Geant4. It will also cover recent advancements in machine learning for particle identification, background rejection, and energy reconstruction. Research gaps identified in the literature will be highlighted to justify the necessity of the proposed work.

Chapter 3: Methodology

This chapter will describe the complete research methodology, including the design and implementation of the Geant4 simulation framework, construction of various detector geometries, and simulation of particle interactions. It will also outline data extraction procedures, performance evaluation techniques, and the development of machine learning models for particle identification and reconstruction. Evaluation metrics, computational tools, and workflow details will be discussed.

Chapter 4: Results and Discussion

This chapter will present the results obtained from the simulation studies and machine learning analyses. It will include comparative performance evaluations of different detector geometries, shower profile studies, particle identification outcomes, and reconstruction improvements achieved through machine learning. The findings will be critically analyzed and interpreted in the context of existing literature.

Chapter 5: Conclusion and Future Scope

The final chapter will summarize the major findings of the research and highlight the contributions made to calorimeter detector development and analysis. It will discuss the broader implications of the work for future high-energy physics experiments. The chapter will also outline potential directions for future research, including extended simulation studies, hardware prototyping, and enhanced ML-based reconstruction approaches.

References

This section will include all cited works in the thesis, formatted according to the required citation style.